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Unified Player Identification Across Field Sports Survey And Proposed Model

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Abstract:
With the popularity of sports industry and development of rapid technological innovations, the player detection has become an important task in sport images/video analysis. AI is now widely used for game prediction, performance analysis, highlight generation, and assistant coaching to improve team performance and decision-making. If the players have been detected accurately, this information can then be effectively used to perform high level analysis. The interest of this paper is to analyze different approaches used to identify and detect the players in sports images proposed and develop a strong player detection system to detect, recognize and track them. The conventional techniques work by detecting the face or body of the players/humans in the picture and then applying state-of-the-art face recognition methodologies to identify the player. Then there are popular systems that work by recognizing the player number on the jersey of players or the bib of the athletes. The approaches have been developed to track the players based on their locations in the field and finally detect them. This study shows the comparative analysis along with the pros and cons of the methodologies discussed in detail. To the best of our knowledge, such a detailed review of player detection comparing various approaches is unavailable in the literature and thus, our contribution claims are significant. A simple and robust automatic technique is proposed to estimate the location of the racing bib. To fulfill the task of athlete identification we have made use of the bib number as well as the facial features. While doing the identification using bib number, facial features are also extracted and a database is built for identification by recognizing face. Extensive test findings are displayed on actual marathon photos with varied player counts in varied positions and illumination settings. It achieves state-of the-art results up to 97%.
Keywords: *Player identification, Face detection, Face Recognition, Jersey Number.*

1. INTRODUCTION

Automated detecting and tracking players in field sport games is very popular and growing multi-million industry. These days the profits from sports industry have increased substantially, so the teams are heavily investing in the process of gathering statistics on their athletes. These statistics predicted during a match, can provide information on players as well as teams performance. Moreover, the trend of capturing pictures during various events is widely popular these days. Whenever a person attends or participates in an event then he captures a lot of images to keep alive the memories. Likewise, during the events like marathons, cycle race and athletics lots and lots of pictures are clicked. Also, these days the organizers upload the pictures captured during these events on their websites or on social media. So, it becomes a tough task to detect and recognize pictures of a particular athlete or player who has participated in such events. For example, if a person participated in such events and he wants to download all those pictures where he is present, it is very difficult to go through thousands of images to find and download the relevant images. So, an automated system would be very helpful to recognize the pictures of a specific athlete and then display only selected images (and not all of them). By looking at any picture we can tell who the person is in the picture but for computers it is a challenging task.

In addition, the sports analysts have discovered that it is not possible even for the games specialists to regularly watch and review the points of interest of the complete game that could prove to be critical for planning game strategies. This is the reason why the volume of research in automatic player detection and tracking is expanding. So, the objective of such research is to understand the need and develop automated systems that understands and examine the behavior of the team and the players, as well as qualities, statistics and game strategies. More generally, our research could be adapted to the chose the right technique for successful identification and tracking of players of any sports match. There are lots of existing systems that solve the above-mentioned purpose. There are some systems that use face recognition to recognize the player and hence they find out who all are present in the picture under consideration [1] [2] [3] [4] [5] [6]. System to recognize the player from facial features are also very popular. Then there are

systems that recognize the player from their jersey numbers or racing bib numbers [9] [10] [11] [12] [13] [14] [15] [16] [17] [18] [19] [20]. It has been observed from extensive study that there does not exist many papers and methods in literature. However, there are similar systems for license plates recognition, scene text detection-recognition, optical character recognition in video and natural images and the working of these systems is quite similar to that of jersey number or bib detection and recognition. The results of such systems are very promising and they solve the purpose of detection of a player/athlete successfully. Also, some systems work by tracking the players [21] [22] [23] [25] [26] [28] [29] [30] [31] [32]. These tracking systems use various factors to track the players during the game. Also, a methodology uses visible light communications on jersey of athletes (called light bibs) which help to identify and recognize them. These are systems that use sensors [33]. Then there are systems that track the players based on the location they take up in the field [24] [27]. These kinds of systems are also very popular and they produce good results.
The layout of this paper is structured as follows. In the following section i.e. Section 2, a short overview of the related work is presented. Various methodologies used in player identification are discussed in Section 3. A novel and robust technique is proposed in Section 4. In the Section 5, the conclusions are made based on the detailed study by comparing results.

2. Related work

The approach to detect a sports person is based on the feasibility of the computer vision. The work proposed by Mahmood et. al. [4] focuses on processing images taken by the audience to detect the face of the player and then recognizing it. These results are then used to evaluate the statistics like age, score, nationality etc. Other methodologies [1], [2], [3] also works by detecting the players based on their facial features. There are many approaches developed by different researchers to detect and recognize the face of human being. Face can be detected by extracting voila jones [34] Hog features, Haar Classifier developed by Wilson et al. [35], a very efficient Multitask Cascaded Convolutional Networks proposed by Zhang et al. [36] and many more different ways. Similarly for face recognition google's FaceNet system proposed by Schroff et al. [37], HOG features and SVM classifier developed by Dadi et al. [38], Haar feature with AdaBoost introduced by Poignant et al. [13] are used for face recognition. Ruiz-del-Solar et. al. [39] and Rahman et. al. [34] shows the comparative analysis of the face detection and recognition techniques proposed by different researchers. Once the face of the player has been recognized then this can be used to identify the player present in the images.
Players can also be identified from their jersey numbers. A technique developed by Ben-Ami et al. [18] for the identification of the marathon athlete by recognizing his bib numbers present on the torso of the athlete. Poignant et al. [13] recognizes players by detection text videos which is then used to person identification. Shivakumar et al. [15] presented a multi-modal approach that works by integrating torso and text detection techniques. The researchers Wrońska et al. [7] and Liu et al. [8] described a methodology for recognition of athletes based on athlete numbers and their face detection. To summarize the work discussed above recognizes the athlete from the jersey number. In the jersey number recognition systems, the approach is to straight away try to recognize the jersey numbers, which is then followed by characters recognition without detecting the number regions. Messelodi et al. [14] preprocess the image to focus on that region which has those pixels which is similar to text background colour (usually white). Then text detection is applied in this region, the results of the previous steps are fed to OCR to detect the jersey number.
There are also works presented for recognition using light bib [33]. Table 1 shows various techniques proposed to detect players.

Table 1: Techniques proposed to detect players during sports.

S. No.	Research Work	Techniques Used	Dataset Used	Major Findings	Research Direction
1	Mahmood et al. [4]	Haar Cascaded Viola and Jones and AdaBoost learning	412 diverse images dataset	Successfully detect faces and recognize to identify players.	Can be used by viewers who capture the game with their smart phones or camera so that they can detect and recognize players. This

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					information helps to display statistics in real time.
2	Markoski et al. [3]	Adaboost	Basketball game images	70.5 % accuracy	Can be applied to analyze basketball games as well.
3	Liu et al [8]		Dataset collected from soccer and basketball games	This work performs better than the state-of-the-art methods.	The system proposed can be implemented to other sports as well
4	Rayhan et al. [9]	YOLOv3 model	2194 raw images in jpg format from BNI ITB Ultra Marathon 2019.	83.0% precision, 81.5% recall, and 82.2% F1score	By increasing the size of dataset and using systems with more computing power may improve the overall network performance.
5	Wrońska et al. [10]	Jersey number by extracting text and face recognition using pixel density of face.	Tested on 55 images that had 68 bib numbers.	The presented work does the double verification which improves the performance of system.	The system proposed can be implemented to other sports as well
6	Messelodi et al. [14]	Segment the region with text background colour, extract text and read these using tesseract OCR	Dataset includes videos recorded for BBC in the Crystal Palace London athletics stadium in 2010	The precision comes out to be 98.9% on undirected videos and 88.7% on directed videos.	The system could be used where it is required to initiate new tracks in a more general tracking system. It also provides a denser labelling of the video.
7	Shivakumara et al. [15]	HOG features and SVM classifier is first used to detect torso and then to detect text location. OCR to detect text.	Marathon images	The proposed system gives better results as compared to existing systems.	Temporal frames can be explored for achieving better results for both text detection and recognition. It is suggested that the combination of classifiers and the conventional OCR can give better results.
S. No.	**Research Work**	**Techniques Used**	**Dataset Used**	**Major Findings**	**Research Direction**
8	Liu et al. [16]	R-CNN framework	A noval dataset of 3567 images	The system gives the digit accuracy of 94.09%	The proposed approach is end-to-end trainable and can be easily extended to other sports.
9	Gerke et al. [17]	To detect player HoG + SVM and CNN to recognize numbers on jersey	10,000 cropped images (from 65 different soccer videos)	Deep learning approaches shows really good results even with smaller datasets like the one presented	Can be extended to other sports
10	Ben-Ami et al. [18]	Face detection, Stroke width transformation for bib detection and	217 coloured images of running race	85% Recall rate	Can be used where text detection problems are partially-restricted

		OCR to recognize numbers	with different resolutions		
11	Santhosh et al. [23]	Pedestrian detected with HOG + SVM for classification, then players are tracked using jersey Color-based detection.		The system detects basketball players in a video accurately and also places them accurately in a 2D top-view court	It is suggested that by adjusting the color segmentation thresholds the identification accuracy could be improved.
12	Zhang et al. [21]	DeepPlayer model for player 2D localization, instance segmentation and identification, the IPOM model for localizing the players' 3D coordinates and the KSP-ID model for the multi-player	APIDIS dataset	Proposed system performs better than the state-of-the-art methods	Temporal information of player could be included to improve the 2D detection
13	Vats et al. [25]	1D CNN model for player identification	84 broadcast NHL game clips at rate of 30 frames per sec and resolution of 1280 × 720 pixels	The system performs better that the current state-of-the-art systems by 9.9%	The proposed system is straightforward to implement and to extend it to other team sports

3. Various Approaches for Player Detection

There are numerous player detection techniques proposed by different researcher. This study analysis some of the different methodologies adopted for recognizing the players in an image.

Player recognition becomes a challenging task because when in action the images are captured in different illumination and different angles.

3.1. Conventional Approach

Detecting and recognizing face: The conventional approach is based on the face recognition system. It can be divided into three phases. In the first phase the image is preprocessed to remove noise and image is converted to gray scale image. Then in the second phase the face of the persons present in the image is detected. In the third phase this detected face is then recognized by matching it with the training dataset. The conventional approach works as follows. The first step reads the image of the player as an input. Then from this Image the face of the player is detected and in the next step the facial features are extracted which are then used to identify the player. To summarize the above discussion, it is observed that a player can be identified by recognizing his face as explained in Algorithm. 1.

A deep learning framework for automatic player identification and activity logging in American football footage is developed by Liu et al. [1] Modern convolutional neural networks are used by the system to identify players, follow motions throughout game footage, and identify jersey numbers. Their method solves issues like occlusions, camera movements, and different angles of view, allowing for effective player

Algorithm. 1. Algorithm to Implement Conventional Approach to detect players using face recognition methods.

Recognizing the player
Step 1: Input the image of the Player. Step 2: Detect the face of the player in an image. Step 3: The location of the detected face is the output of the above step. Step 4: Extract the facial features of the face. Step 5: Match the face of the player with the training dataset. Step 6: The player has been recognized and the name of the player is the output of the system.

analytics without the need for human involvement. It is a useful tool for coaches and analysts to extract comprehensive player statistics and performance insights from game recordings because of the excellent accuracy and robustness of the experimental results. An automatic face detection and identification system designed specifically for cricket players is presented by Haq et al. [2]. The system successfully recognizes players in difficult situations, like changing illumination and dynamic game settings, by applying deep learning algorithms. To deal with occlu-sions and varying player orientations, the suggested model integrates face detection with strong recognition techniques. The method's high accuracy, as demonstrated by testing on a large cricket dataset, opens up possibilities for player tracking, broadcast improvement, and fan interaction. In a field with little previous research, this study offers a workable technique for automated player identification in cricket.

Ren et al. [3] introduces a novel method for detecting and identifying inappropriate postures and movements of table tennis players using soft computing techniques. The approach combines sensor data with machine learning models to monitor players' biomechanics and flag potentially harmful or inefficient actions. This system aims to improve player safety and performance by providing real-time feedback and coaching insights. Through rigorous experiments, the method shows high accuracy in classifying postures, contributing to injury prevention and training optimization. Proposed work is a significant step toward integrating intelligent monitoring in sports training environments, particularly for fast-paced games like table tennis. The automation of sports video analysis is greatly advanced by this study. An augmented reality sports broadcasting system was created by Mahmood et al. [4] to automatically recognize and identify players during play, and then display the players' personal information. There are four main steps to the proposed suggestions. Every player in the picture is identified in the first step. A face detection algorithm finds each player's face in the second step. In the third step, we match player faces with a database of player faces that also contains each player's person-al data using a facial recognition algorithm. Step four involves retrieving each player's personal information based on the outcome of the face matching. With the use of this application, viewers will be able to read details on players, like their name, nationality, age, and greatest score. This system is intended for use in baseball games. While the player face recognition system uses the AdaBoost algorithm with nearest neighbor classifier for classification and linear discriminant analysis for feature selection, the player and subsequent face detection tasks use the AdaBoost algorithm with haar-like features for both feature selection and classification. In-depth tests are conducted using 412 different digital camera photos captured during a baseball game. Players of various sizes, poses, lighting situations, and facial expressions may be seen in these pictures. The accuracy of player and face detection is high across all scenarios; however, frontal or nearly frontal faces of detected players are required by the face recognition module. Restricting the head rotation generally results in a high level of system accuracy.

Boosting methodology, one of the most advanced methods for object detection, is used in face detection. The foundation of the face detection technique is the feature subspace, which maps the face image to a certain feature space. The distribution law in feature subspace is used to distinguish between faces and non-faces. The basic characteristics utilized are similar to the Haar basis functions proposed by Viola and Jones [34]. Wilson et al. [35] Proposed improved face detection technique. Zhang et al. [36] developed an efficient face detection methodology Multi-task Cascaded Convolutional Networks. It gives promising results even in low resolution images. So, after detecting the face, next step is to recognize it to identify the person. FaceNet [37] is state of the art face recognition system developed at Google. Harihara et al. [38] suggested utilizing SVM classifier and HOG features to increase the face recognition rate. Ruiz-del-

Solar et al. [39] presented another methodology to recognize face by extracting of human facial features based on eigen space and then recognizing it. In a comparative analysis of facial recognition algorithms, Mahmood et al. [40] compared AdaBoost with linear discriminant analysis, principal component analysis (PCA) and local binary pattern (LBP). The results showed that PCA performs well in pose variation detection, AdaBoost was efficient at identification of faces in low resolution images and LBP had lower recognition accuracy than PCA and AdaBoost. The study showed LBP did not classify face images that had size 20x20 pixels and below. For LR images of size 20x20, 10x10, and 5x5 pixels, the AdaBoost-based algorithm performed better than the PCA and the LBP. And for frontal face, AdaBoost-based algorithm exhibited 100% classification accuracy, even for size of 10 × 10 and 5 × 5 pixels.
There are similar systems developed by various researchers to identify players based on their facial features. Santosh et al. [5] has proposed an automated system for player detection and then tracking him in basketball game. Markoski et al. [5] applies the adaboost algorithm for detection of players in basketball player. Similarly, Ballan et al. [6] proposed an auto-mated methodology for identification of players based on their facial features.
The following block diagram Fig. 1 showcase this procedure.

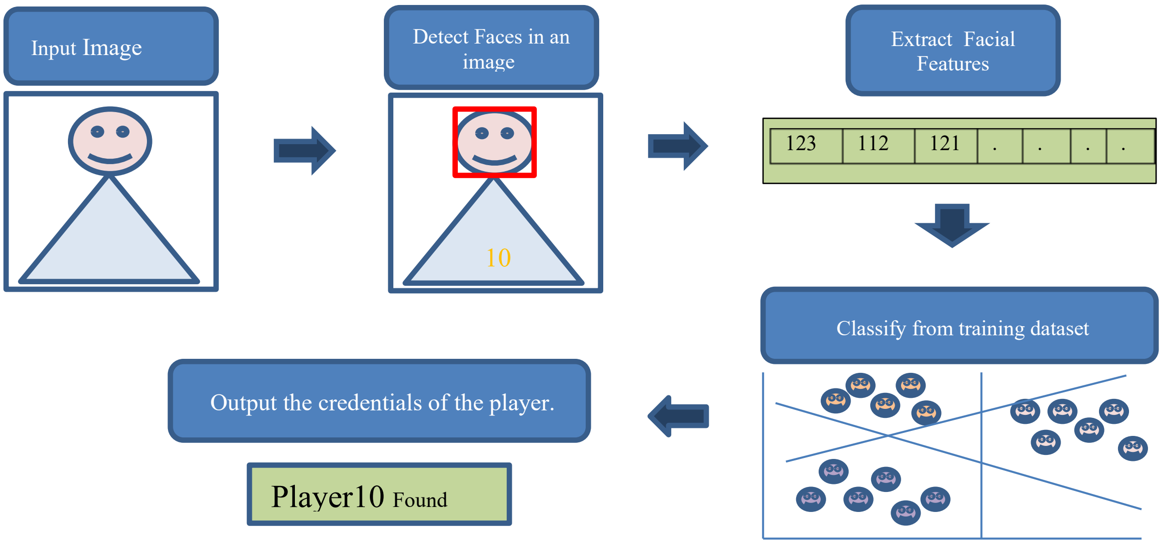

Fig. 1. Recognition based on facial features

This methodology is largely dependent upon the performance of the face recognition system. Better the efficiency of the face recognition system better will be the results of player detection. However, if the face of the player is not visible which usually happens when the player is in action, then this approach will not work. We know that in sports event each participant wears a specific jersey and each participant has a unique jersey number. Various systems have been developed that works by detection a player based on the jersey number. Following methodology works upon this idea.

3.2. Conventional Approach Detecting Jersey Numbers/ Bib number

In this section second, the methodology described is based on recognizing the jersey number of the players.
There are various techniques developed by researchers to detect the jersey number of the players and hence recognize them. This technique works in four phases. The first phase implements the techniques that searches the text in the input image. Then in second phase this text is passed through the OCR system. Then in the third phase this text is compared with the jersey number of the player to check if the player is present in the image or not. Finally in the fourth phase the detected candidate regions are recognized. The methodology discussed above can be summarized in the Algorithm 2 which describes the detection of a player based on jersey number.

Liu et al. [8] presented JEDE, a novel universal jersey number detection system designed to operate across multiple sports. Their method tackles issues such as different jersey designs, numbers obscured by players or activity, and different lighting conditions.

Algorithm 2. Algorithm to detect the player using his jersey number

Recognizing the player

Step 1: Input the image of the Player.
Step 2: Detect the face of the player in an image.
Step 3: The location of the detected face is the output of the above step.
Step 4: Extract the facial features of the face.
Step 5: Match the face of the player with the training dataset.
Step 6: The player has been recognized and the name of the player is the output of the system.

To precisely find and identify jersey numbers from video footage, the system combines deep learning models with sophisticated image processing algorithms. When compared to current techniques, JEDE exhibits great accuracy and robustness in tests conducted on multiple sports datasets, indicating promising applications in player monitoring, sports analytics, and broadcast enhancement. The system's scalability and versatility, which allow it to be adjusted to different sports without the need for sport-specific tuning, are highlighted by the authors. All things considered, the study makes a substantial contribution to automatic number detection, tackling practical issues and broadening the application of computer vision in athletic settings.

Rayhan et al. [9] proposed a deep learning-based method specifically focused on recognizing racing bib numbers in sports events. Their research uses convolutional neural networks (CNNs) to reliably identify and categorize bib numbers from race images, addressing problems including low image quality, motion blur, and a variety of bib designs. The model design and training procedure are described in depth in the paper, along with how well it handles the particular difficulties presented by fast-paced outdoor racing events. Promising recognition accuracy is demonstrated by experimental findings on a dataset of racing photos, demonstrating the approach's usefulness for participant monitoring, race management, and result verification. This study opens the door for more automated and effective racing data collection methods and offers insightful information about using deep learning for digitizing sporting events.

Messelodi et al [14] proposed a system for player identification by scene text recognition and tracking to identify athletes in sport videos. The first step is to narrow the region of search for text detection. For this the researchers have used the fact that the text i.e. athlete's bib is usually black-on-white background. By taking use of this feature, attention is drawn only to the image's unsaturated color regions, especially the white ones. To obtain these zones, all the pixels with low saturation and a reasonably high brightness are chosen. An alternative criterion must be used in situations when the text foreground and background have polarity other than black-on-white. This involves applying an approximate color quantization approach to extract the image's pixels that roughly correspond to the text background color. This narrowed area is used to search for the text. Then this extracted text is interpreted using OCR. The OCR used for the purpose is Tesseract [41]. Then from this identified player's unique number the identity of the player if identified.

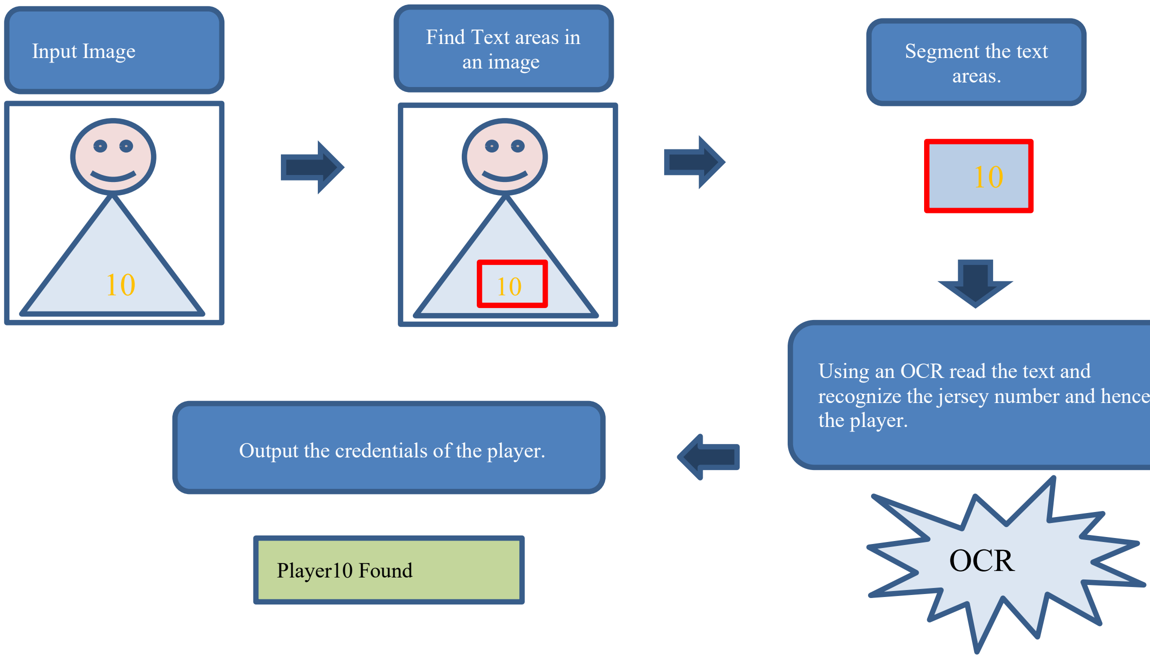

Fig. 2. Recognition based on Jersey number by detecting torso

Shivakumar et al. [15] presented an approach that uses multi-modal to integrate torso and text detection in a novel way to achieve promising results. This approach worked in two stages. In the first stage, the torso of the player was detected. To achieve this, HOG features were explored and SVM classifier was used to detect upper body. Then from upper body, fore-ground is segmented using Grab Cut method was applied. After this, to detect the torso, the pictorial structural model was used. In the second stage, text was detected using the HOG based text detection method descriptors and

classifiers and recognized on the torso. For the tested images F-score varies from 0.77- 0.87.
The researchers Wrońska et al. [7] described a project for recognition of athletes based on athlete numbers and their face detection. The images were first preprocessed to convert them to gray scale and by applying histogram equalization. This technique worked in two phases. In the first phase contours i.e. all white or black areas were extracted to decide whether it was a digit. Then all these numbers that fit the presented number model were analyzed by classifier (Tesseract OCR) to recognize the athletes from their t-shirt number. And in the second phase it made use of face detection technique (Color Quantization method) and recognized the athlete so as to make sure the athlete recognized was not faulty (to overcome situations like when two athletes exchange their t-shirts). The results were as follows: % of Numbers Identified is 94.12 and % of Digits Identified, % of faces detected and recognized is 64.86 for men and 74.14 for women.
The researchers in [5], [12] and [13] also presented different techniques to recognize the jersey number of the players in different sports.
The block diagram in Fig. 2 showcase this procedure.
Apart from the above way of detecting the jersey number a technique was developed by Ben-Ami et al. [18] for the identification of the marathon athlete by recognizing his bib numbers. To detect the location of race bib, firstly a Haar face detector was used to detect the location of the face of an athlete. Then the bounding box of dimensions 3. (face height) X 7/3. (face width), located at 0.5.(face height) below the face was found out and then RBN location was found out using stroke width transform (STW). This bib was then processed and fed to the Tesseract OCR engine to recognize the bib number. Then this bib number was used to recognize the athlete. Images from running races found on the Web were collected to test this meth-od. The researchers showed the results that F-score computed for the test images varies from 0.57-0.63. These steps are summarized in the following Algorithm 3.

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Algorithm. 3 Algorithm to detect the location of the bib on players body and then recognize it.

Recognizing the player
Step 1: Input the image of the Player. Step 2: Detect the location of the face of the player in an image. Step 3: Estimate the torso of the player using the formula from the dimensions of the face location in above step. (face height) X 7/3. (face width), located at 0.5.(face height) below the face Step 4: Find the location of the bib on the torso using stroke width transform (SWT). Step 5: Pass this bib through OCR system like Tesseract and read the bib number of the player. Step 6: Match this bib number with the name of the player to recognize he player. Step 7: The player has been recognized and the name of the player is the output of the system

The block diagram of Fig 3 shows the pictorial representation of the bib detection and bib number recognition technique. Various techniques for detection of bib are proposed by Rayhan al el. [9], as well. The drawback of this methodology is that is the jersey/bib is folded or is fully or partially obscured then the jersey number of the player will be recognized incorrectly. Moreover, if the jersey of a player is worn by another colleague, then this fails. But if the number is recognized correctly this gives promising results even if the players face is not visible or even if he is facing backwards.

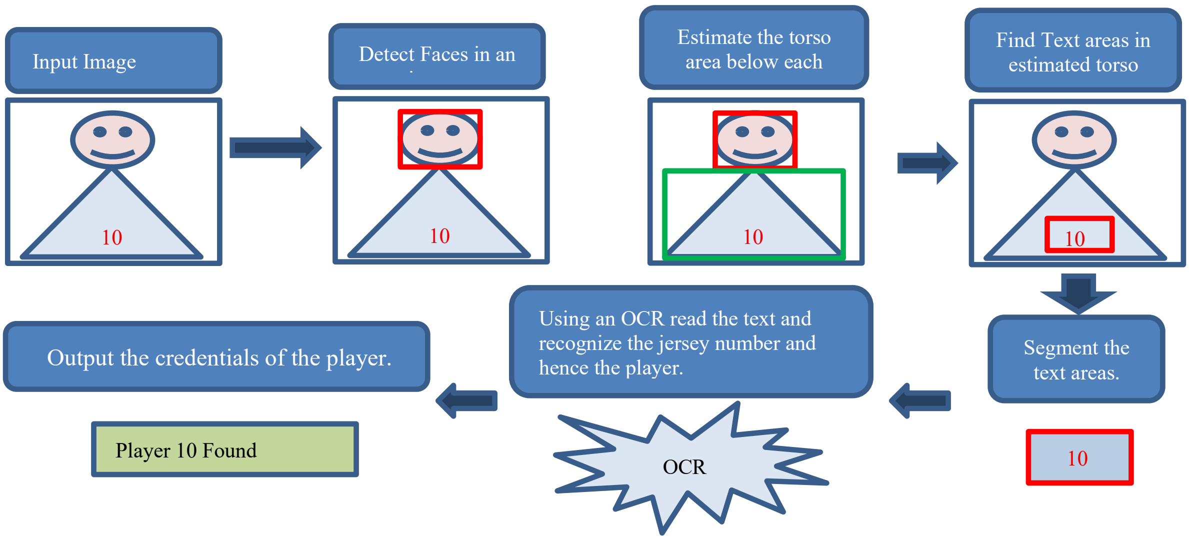

Fig. 3 Recognition based on bib number by estimating torso location

3.3. Detecting location of the player

It is clear from the technologies outlined above that it is difficult to identify players, particularly in overview shots where face identification is impractical owing to poor resolution and jersey number identification suffers from motion blur, poor resolution, and improper player stance. There are also techniques used to detect the players by tracking them. This algorithm is described below in Algorithm 4.

[19] Khan et al. proposed Player identification in interactive sport scenes using region space analysis prior information and number recognition. Another methodology "Soccer players identification based on visual local features" is proposed by Ballan et al. [6]. Person re-identification using group information is developed by Bialkowski et al [24].

A technique to enhance visual recognition by merging spatial constellations with the jersey number was presented by Sebastian et al. [20]. With this approach, a spatial constellation is represented as a histogram of the relative positions of each team member. Convolutional neural networks are thus used to combine this constellation-based recognition with jersey number recognition. When comparing the accuracy with jersey number recognition alone, it increases from 0.69 to 0.82.

There are other methodologies that too work in similar manner. Techniques proposed in [21], [22] and [25] work by tracking the location the player in focus in the field in sports videos. Moreover, some

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techniques [23], [24], [26] [30] [31] and [32] work by detecting the players in the field based on the team activity of the player and then quantifying and analyzing the performance of an athlete during the game. This methodology is showcased in the block diagram below Fig. 4

Algorithm. 4 Algorithm to detect the track players on the field and then identify them.

Recognizing the player
Step 1: Input the image of the Player.
Step 2: Detect all objects in the soccer field (players, soccer ball, referee, and background).
Step 3: Classify and exclude the background from the playfield.
Step 4: Create a coherent tracking framework.
Step 5: The player has been recognized and the name of the player is the output of the system.

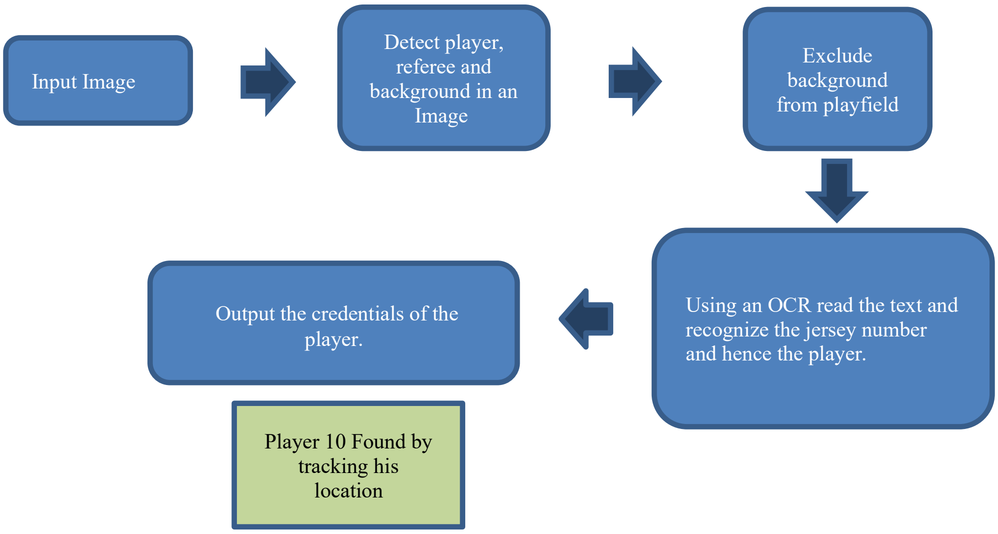


Fig. 4 Recognizing by Detecting the Location of Player

3.4. Other Aprroaches

Researchers have developed other methods to detect a player. One of those approaches is explained below. Fu et

al. [33] proposed LightBib, a novel marathoner recognition system. This system made use of visible light communications (VLC). Each runner wore a pair of light strips which transmits the runner's ID with VLC. A transmitter was used to send the images captured by different cameras with an on-off pattern at a certain frequency (using frequency shift keying modulation technique). The received images were then post-processed, where image areas corresponding to a certain runner were detected and recognized by extracting the ID embedded in the pixels with very high accuracy. The experimental results indicate that the average recall to identify each of the 5 runners in a single image was close to 90%.

3.5. ANALYSIS AND DISCUSSIONS

The following table Table 2 summarizes and shows the comparative analysis of the techniques discussed above.

Table 2: Summary and comparative analysis of various methodologies for Player Recognition.

Sr. No	Methodology	Detection is based on?	Performance	Major Findings	Future Research Direction
1	Conventional Approach	By recognizing the face of the player/athlete in an image.	Depends upon the face recognition technique used. If face is not visible or if facial features cannot be extracted due to low resolution, occlusion etc., this technique won't work.	This research makes the automation of player identification applicable across several sports.	This technique can be implemented on various sports. However, if face is not visible then this method will not work.
2	Detecting Jersey Numbers/ Bib number	By identifying the jersey number/ Bib number present on the jersey/ torso of the players.	Completely dependent on jersey number detection technique and OCR used. If jersey number is not present or is occluded this methodology will not work.	This automated system of player identification is applicable across several sports by detection the jersey number or bib number. But if jersey number or bib is not visible the system fails.	This methodology can be extended to different sports. If the player is identified successfully then this information is helpful in various predictions and analysis.
3	Detecting location of the player	By tracking the location of the players by making use of region space analysis, local information etc. along with jersey number.	Depends upon information like position of players in the game etc. If this data is not available this methodology doesn't provide promising results.	By tracking the location of the player as well as referee various sport Analysis are done.	Game strategies can be understood and winning strategies can be generated. Successful predictions and analysis can be made in various sports
4	Other Approaches	One technique uses visible light communications to detect the athletes.	Needs to install pair of light strips which transmits the runner's ID with VLC.	Players are automatically detected. But special hardware installation will be required.	This technique works well in athletics.

Research Gap: From the above comparative analysis, we can see that the player recognition techniques work either by recognizing the players either from their facial features or by detecting the jersey number and hence applying OCR to read jersey number to recognize the athletes.

Our Contribution: To develop a technique to recognize an athlete based on facial features and bib number. The developed technique would first detect the face and then the jersey number would be detected. If found then the player will be recognized from the jersey umber. Then the facial features would be extracted and dataset would be updated to associate jersey number with the facial features. If jersey number is not found then facial features would be extracted and the player would be recognized from their facial features. The following sections explain this methodology in detail.

4. A Novel Technique to Recognize an Athlete Based on Face Recognition and Bib Number

4.1 Algorithm

The algorithm for detection of the racing bib location, works in following phases by first detecting the human face and from the location of the face the torso area of the athlete is detected and then torso area is segmented to find the location of the bib. Once the image has been scanned for recognition of an athlete from the bib number, still some candidates are left that has not been recognized because the bib could not be found due to certain reasons. In such cases the athlete would be recognized from his facial features. The following block diagram Fig 5 shows the methodology that would be followed to recognize an athlete using his bib number as well as his facial features. First of all, it is required to create a dataset for the athletes. This dataset will be used to train the system. In the initial stage when an athlete has been recognized from his bib, the first step is to detect the face of the athlete. This detected face of each athlete will be stored in a separate location. For example, if n number of images of an athlete with bib number x has been identified then these face images will be stored in a location with the name x. This data will then be used for extracting the facial features of the athlete.
When we have labelled dataset of athletes, then this labelled dataset will be used for training. And this data will be fed to the system that extracts the facial features of an athlete. When we have system trained with this dataset, then it can be used to recognize and athlete from his face if bib is not visible in an image.

Step 1: Detect the face location to estimate the torso and localize the Bib/Jersey number.

The Bib/Jersey number is normally present on the torso of the player. So if try to locate the bib and recognize the text from an image it would be a tedious task. To ease our job the face location is detected first and torso area below the face is estimated [16]. Then on this torso area the text localization technique is applied to detect the players Bib/Jersey number. Kaur et al. [22] shows the comparative analysis of various face detection techniques that shows a deep learning model built on a cascaded structure called MTCNN—Multitask Convolutional Neural Network shows outstanding results. So, this model is used for face detection. This method relies on resizing photos to various scales, which creates an image pyramid of the associated facial image. The three steps identified in the MTCNN model [36]: -
a. The first stage, Proposal Network (P-Net), returns the bounding box coordinates. It iterates the process section by section by shifting the 12 x 12 frame by 2 pixels to the right or down at one go.
b. In the second stage, Refine Network (R-Net), the co-ordinates are refined. As a result, this stage produces fresh, quite ac-curate bounding boxes along with the level of confidence in each of them.
c. The third stage. Output Network (O-Net), generates output includes the bounding box coordinates, the coordinates for the five face landmarks, and the confidence level for each box.
After detecting the face of the athletes, the torso area bounding box is estimated using the formula below.
Left Top corners coordinates (Xtorso, Ytorso)
Xtorso = Xface – Wface/2.................................(1)
Ytorso = Yface + Hface....................................(2)
and width (Wtorso) and height (Htorso) of Torso
Wtorso = 2*Wface..(3)
Htorso = 3*Hface..(4)
Once the torso area has been estimated, then the next task is to localize the Bib/Jersey Number in this area and draw the bounding boxes around them. For this purpose, a deep learning CNN model is used which is trained to localize the text in an image. The implemented Convolution Networks has three

convolutional layers. Low-Level characteristics like edges, color, gradient direction, etc. are captured by the first layer. The next two levels concentrate on both result refinement and High-Level characteristics. The strength of the activation function, pooling function, and convolution function form the basis of a CNN, a deep neural network. CNN models feed each input through a series of convolution layers with filters (Kernels), pooling, fully connected layers (FC), and application of activation function in order to classify an input with probabilistic values between 0 and 1(Moya Rueda et al, 2018) [23]. In kernel convolution, an image is taken as an input, small matrix of numbers called a kernel or filter is applied on it using stride. In order to down sample the feature map's feature detection,

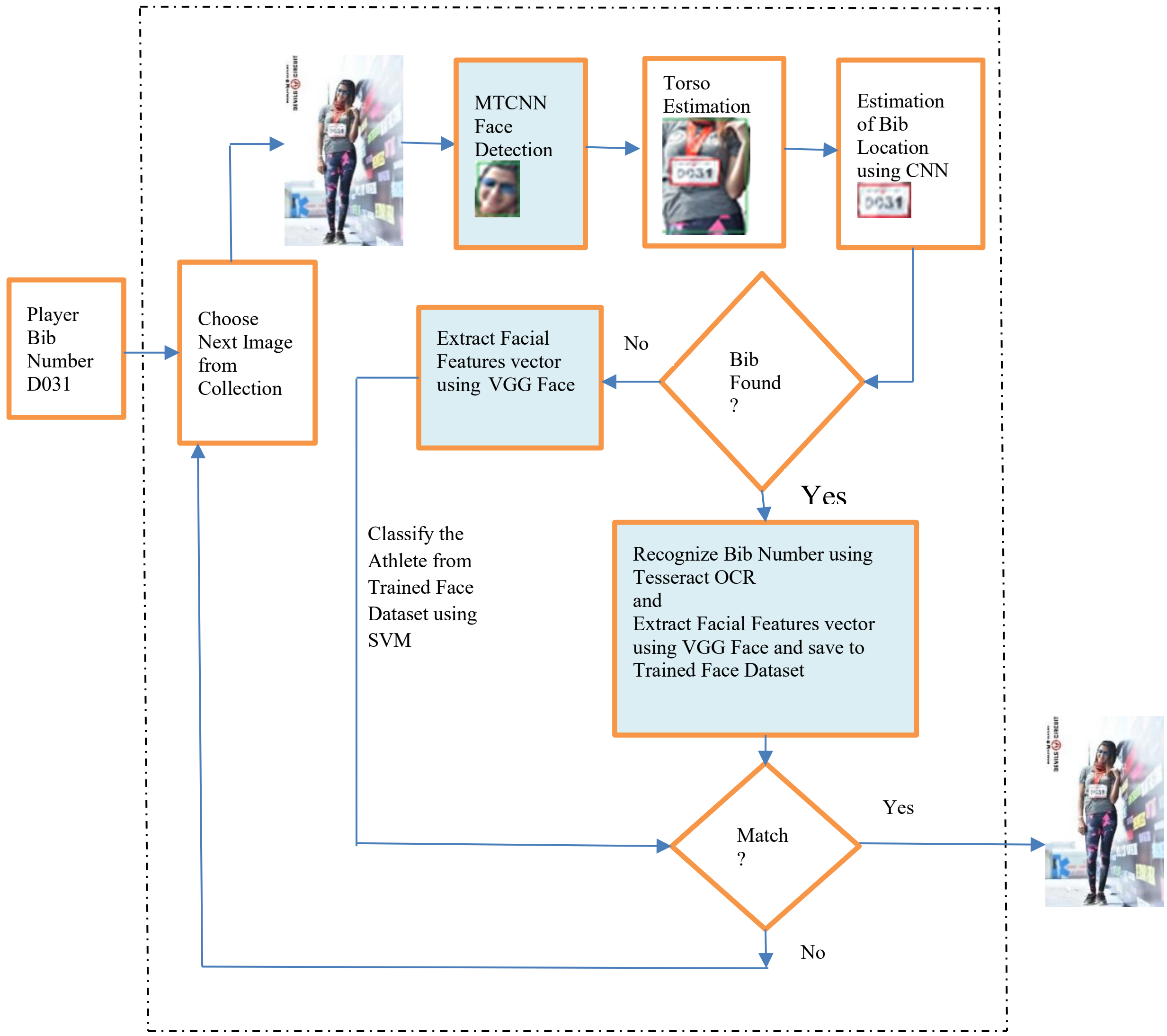


Fig. 5. Searching the images of the desired athlete.

pooling must be used to summarize the features' presence in each feature map patch. The succeeding feature map values are calculated using the following formula, where f represents the input image and h represents our kernel. The result matrix's row and column indexes are denoted by m and n, respectively.

$$G[m.n] = (f * h)[m,n] = \sum_j \sum_k [\![h[j,k]f[m-j,n-k]]\!] \qquad (5)$$

The block diagram Fig 6 shows the model architecture of simple 2D CNN having three layers implemented to localize the location of bib number. Since we have very small area left to be searched for text area, this simple 2D CNN model shows very promising results. This model was trained on dataset containing only torso area with 16,000 images. The labeled dataset for torso and bib area localization is not available publicly. So, this primary dataset was prepared on images collected from a marathon event.

The graph in Fig 7 shows that the system achieved the accuracy of 92.97 % when run on around 153 epochs. It is clear from the accuracy and loss graph that the curve achieved stability on reaching 153 epochs. The output of implementation of face detection, torso estimation and text localization steps is shown in Fig 8.

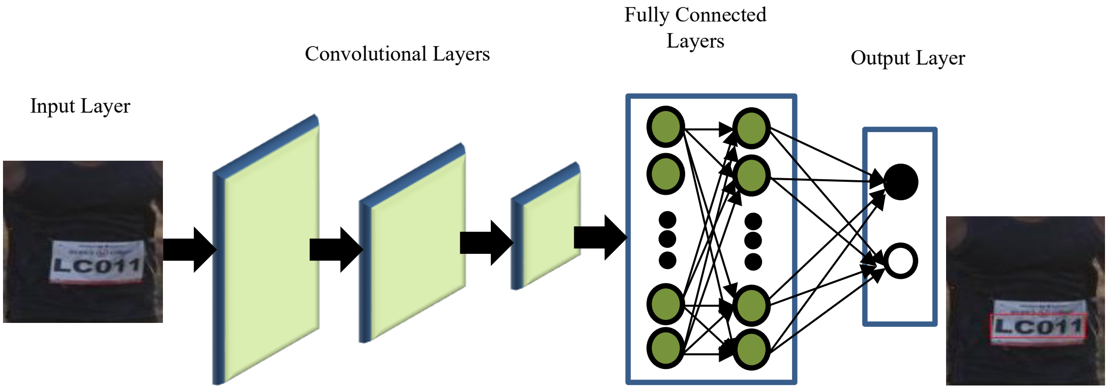


Fig. 6. Architecture of CNN for text localization

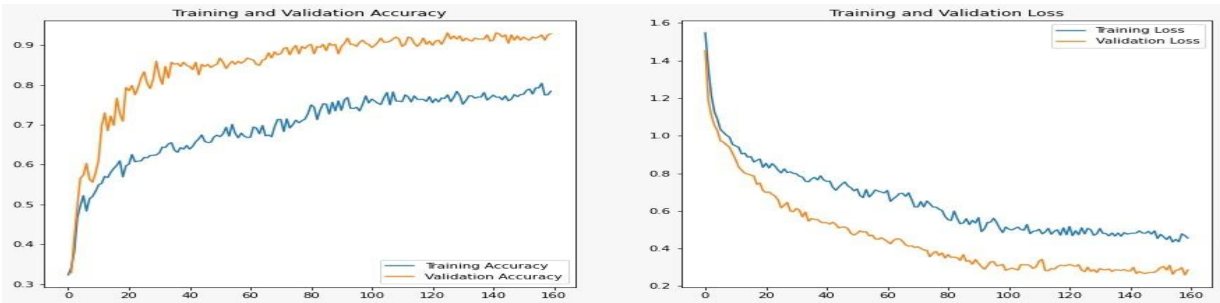


Fig. 7. Accuracy and Loss Curve for Torso dataset including 16,000 images for bib localization

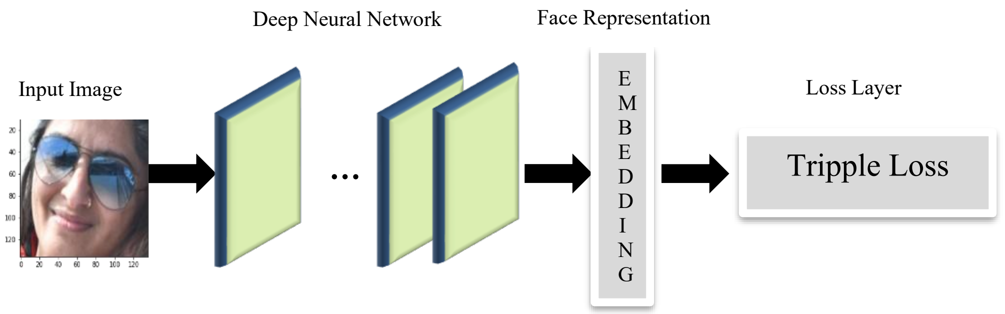
Fig 8. Detecting face, estimating torso and localizing Bib/Jersey number location

Step 2: Find the Facial Features

Google created FaceNet, a deep learning-based face recognition system that converts photos of faces into a condensed Euclidean space where face similarity is directly correlated with distance.

128-dimensional embedding vector rather than categorizing faces into groups. Face similarity increases with the proximity of two embeddings in this space.

A deep Convolutional Neural Network (CNN), frequently based on designs such as Inception or ResNet, forms the foundation of FaceNet. Three images—an anchor, a positive (identical to the anchor), and a negative (identical to the anchor)—are used to train the network using a triplet loss function. The loss efficiently clusters similar faces while separating distinct ones by ensuring that the anchor is closer to the positive than to the negative by a certain amount.
FaceNet does not require retraining for new identities once it has been trained and may be used for face verification (1:1 matching), recognition (1:N), or clustering. Because of its scalability and resilience, it is widely utilized in real-world applications and achieves good accuracy on common benchmarks like LFW. FaceNet essentially turns facial recognition into a vector comparison problem, which makes it practical and very successful.



Step 3: Case1: If Bib/Jersey number found- Player Detection and Labelled Dataset Formation

In the above steps we have successfully constructed the database including the bib number and associated face. These results are used to compare to the bib number of the desired athlete. If it matches then the athlete is present in the image else, he is not as shown in Fig 10. Tesseract [41] OCR is used.

Step 4: Case 2: If Bib/Jersey number not found

In case of those images where bib is not visible the facial features extracted in step 2 will be then used to compare to those of the athlete we are looking for. If it matches then the athlete is present in the image else, he is not as shown in Fig 11.

Fig. 9. FaceNet Architecture

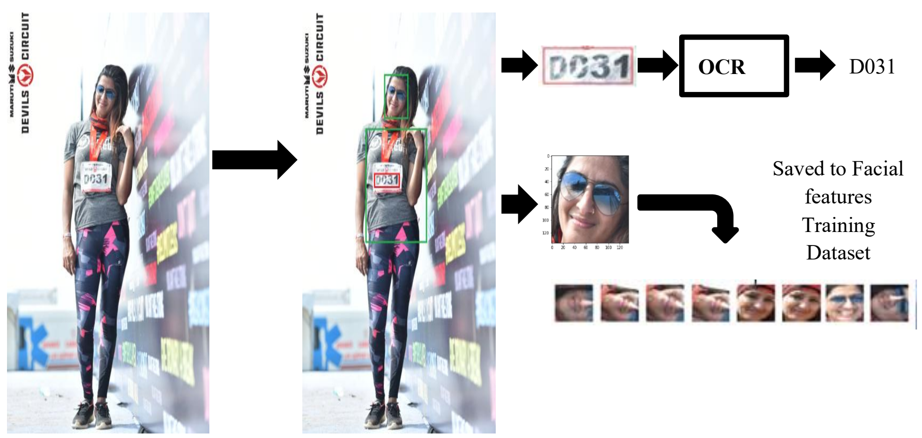


Fig. 10. Recognizing Player from Bib

Fig. 11. Recognizing Player from Face

4.2 Dataset and Evaluation

The system has been trained and validated on the dataset comprising 30,000 images from a marathon event. The data set has been carefully evaluated and all the duplicates have also been removed. All the images are in jpeg format. The dataset to train the model for bib localization is the primary one. Input images in the training dataset have been obtained by cropping the complete image of the scene using the technique explained to estimate the torso area. The output images in the training dataset have been obtained by manually marking the location of the bib. This training dataset comprises of labelled 16,000 images. Then it has been tested on another 4000 images.

4.2 RESULTS AND DISCUSSIONS

In this paper a new system to detect an athlete from his bib number and facial features in natural image collections from a running sport events, is presented. It is shown here that by exploiting the features of face as well as bib number on the torso of an athlete, an efficient athlete recognition system has been developed. Table 3 compares the proposed technique with the existing ones.

Table 3: Comparing the proposed technique with existing

Author	Year	Methodology	Results
Haq et. al. [2]	2024	Haar features + AdaBoost for face & player detection and LDA-based feature extraction + PAL-AdaBoost for face recognition	PAL-AdaBoost achieved 91% accuracy (precision, recall, F1 in low-90s).
Liu et. al. [8]	2023	2-stage neural network. 1st to detect player and 2nd to recognize jersey number	87.9 % for player detection and 91.7 % for jersey number recognition
Liu et. al. [12]	2022	Fully Convolutional Network for 2-digit jersey number detection and recognition	91.65% AP for jersey digit detection
Rayhan et. al. [9]	2020	YOLOv3 model to detect racing bib and another YOLOv3 model to recognize numerical digit.	83.0% precision, 81.5% recall, and 82.2% F1score
Liu et. al. [16]	2019	R-CNN to identify player from jersey numbers	of 94.09%
Proposed Work	**2025**	**MTCNN for face detection 2D CNN for bib localization FaceNet for face recognition**	**97% for player detection and 96% for player recognition**

5. CONCLUSION

From the exhaustive study in the field, it has been observed that methodologies are being used popularly that tell if the player is present in an image or not by recognizing the facial features of the athlete. And of course, there are efficient methodologies developed to recognize the athletes from their jersey number or race bib numbers. For this it is first required to narrow the search area i.e. around the torso of the athlete using different methods. And from there the text of the jersey number or bib number is detected. After detecting the text, jersey numbers are recognized using OCR systems and if this number matches to that of an athlete in question, then as a result it is concluded that this is an image of that particular athlete.

But the first one does not work well if the face of the athlete could not be recognized due to reasons like if the face is not properly visible, if it is hidden, if features could not be extracted due to poor luminance. Moreover, face detection technique chosen should be able to detect the faces of an athlete even if the image is of low resolution.

And the second technique does not give good results in situations like when the jersey numbers are fully or partially hidden, if the picture is taken in such a way that the front or the back body is not visible where jersey number is present, if a part of jersey number overlaps, if the jersey number is confused with the advertisement of sponsors or other prints on the athlete's jersey or if jersey number is not present at all.

In this study a new approach is developed to detect an athlete from its bib number as well as facial features. The ideas demonstrated in this study can also be implemented on other sports by training the system to recognize the jersey number rather than the bib. This methodology also solves the problems of previous study in those scenarios where the bib number is partially-restricted. Because in such cases the facial features are put to use. Moreover, in those cases where bib is accurately recognized, the facial features are saved in the face dataset of that particular athlete which will further enhance the performance of face recognition system. As far as limitations are concerned, the system totally depends on the performance of the face detection, OCR and face recognition systems. In addition, cases have been found where face occluded but bib is clearly visible. In this situation athlete cannot be detected since face will not be detected. In future research a system could be developed to overcome such scenarios too.

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